

## Introduction

In order to optimize the design of complex shapes, there can be a large number of variable which can lead to difficult optimization problems. Simplifying to a smaller dimensional latent space can dramatically increase the efficiency of the optimization.

One major difficulty with this space is the lack of large quantities of data to use as a training set, which can result in poorly trained models.

Using a Generative Adversarial Network (GAN) model we seek to determine a latent space of smaller size that will make the optimization easier.

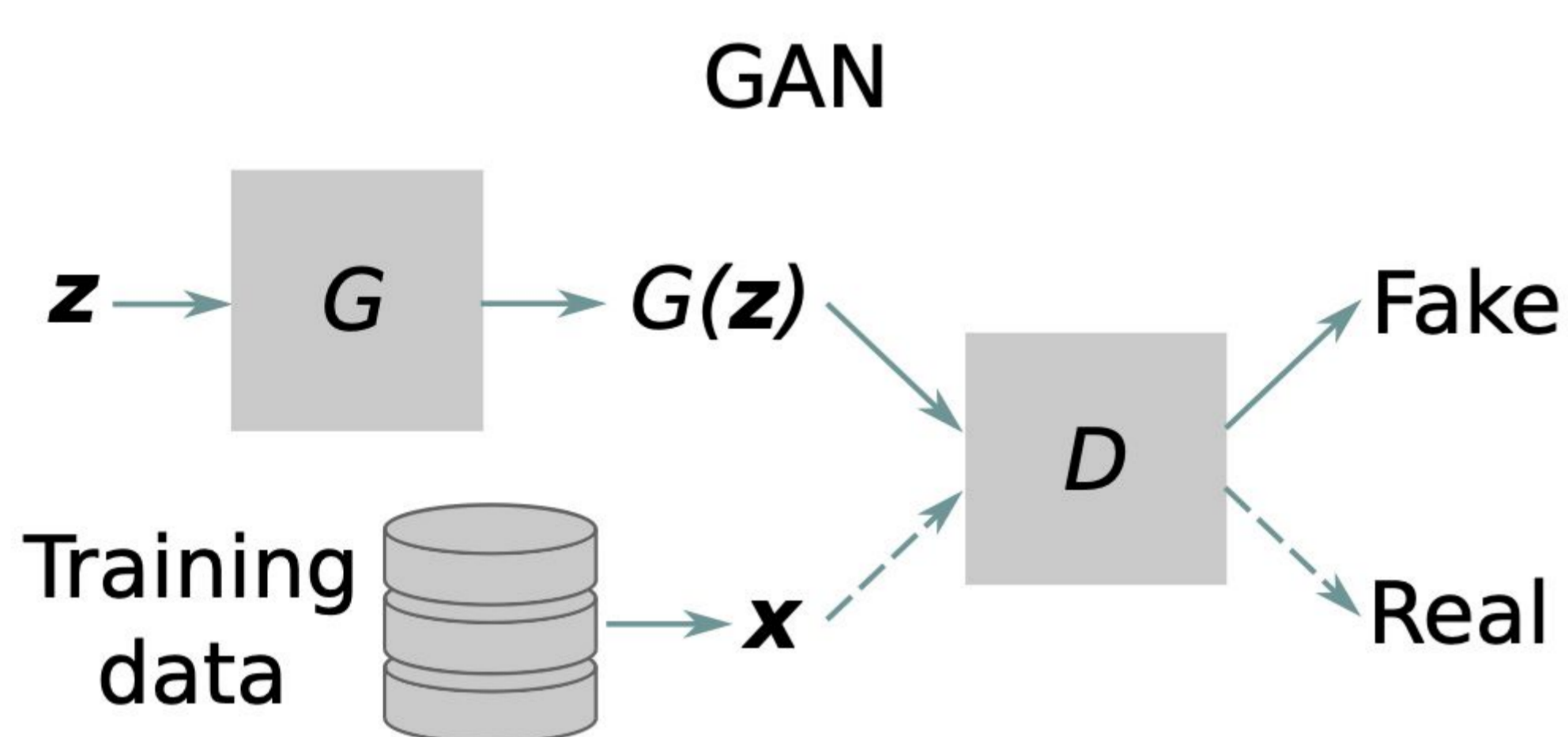


Figure 1: Outline of GAN model design

A GAN model is based on two networks, the generator (G) and the discriminator (D), which work together to convert a latent space into a design.

The role of the generator is to take the latent space along with some noise variables (Z) and convert it into a plausible design.

This generated design  $G(z)$  is then passed into the discriminator, whose role is to determine whether the generated design is real or fake.

The generator and discriminator are trained in a competitive process, with both networks refining at the same time.

## Research Aims

- Design and train a GAN model to generate redox flow battery topologies
- Discover novel channel design to optimize energy density and efficiency
- Generate a training set of various topologies to use for training a GAN model

## Training Data

- Use SolidWorks to create DXFs halves of predefined topologies using Design Tables
- Combine the various halves in all possible combinations using MATLAB
- Interpolate points in between all vertices to give more data for GAN model to use

## Results

- Generated 6 distinct topologies with 25 variations each based on angle geometry
- Used MATLAB to generate 22,500 possible combinations of different topologies

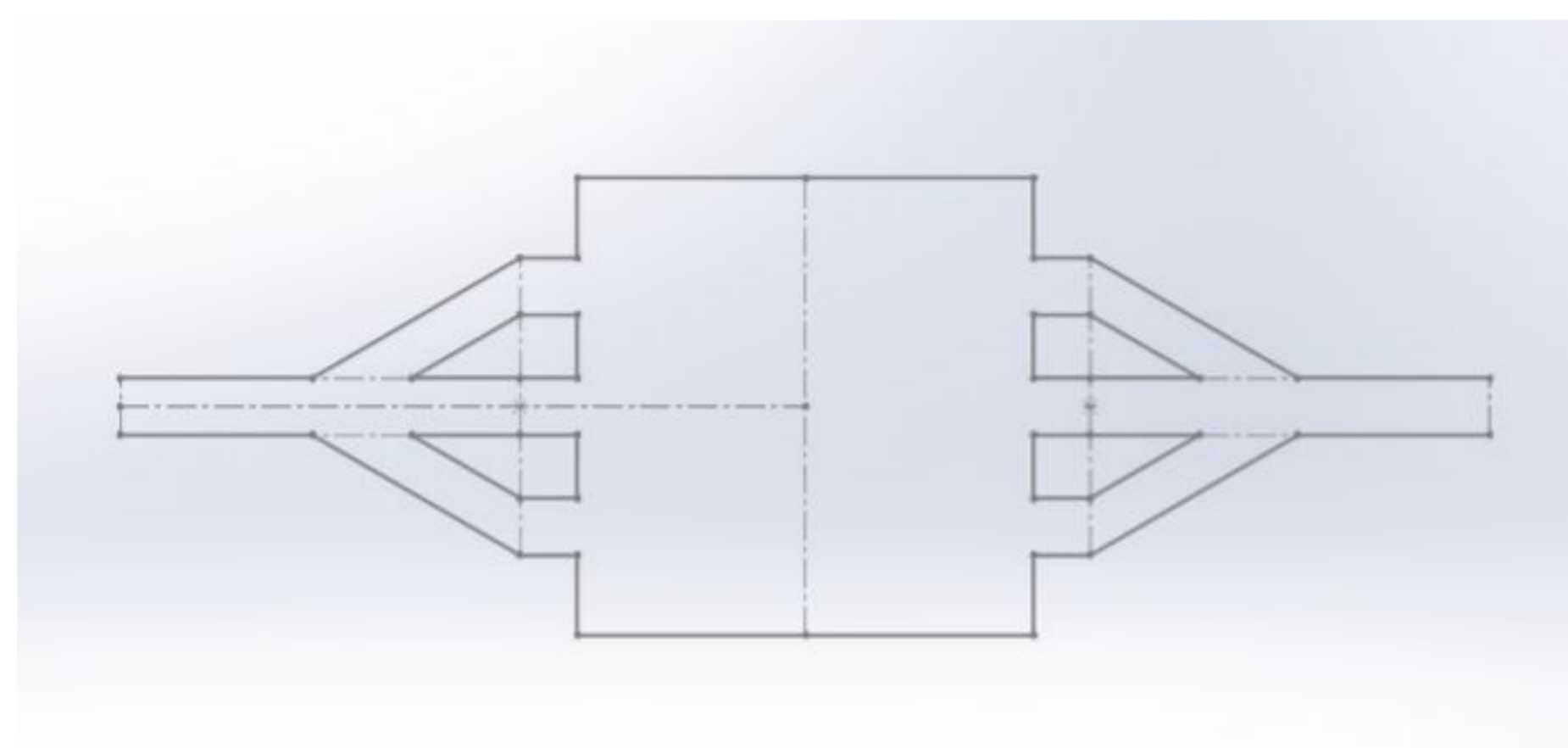


Figure 2: Example of SolidWorks design

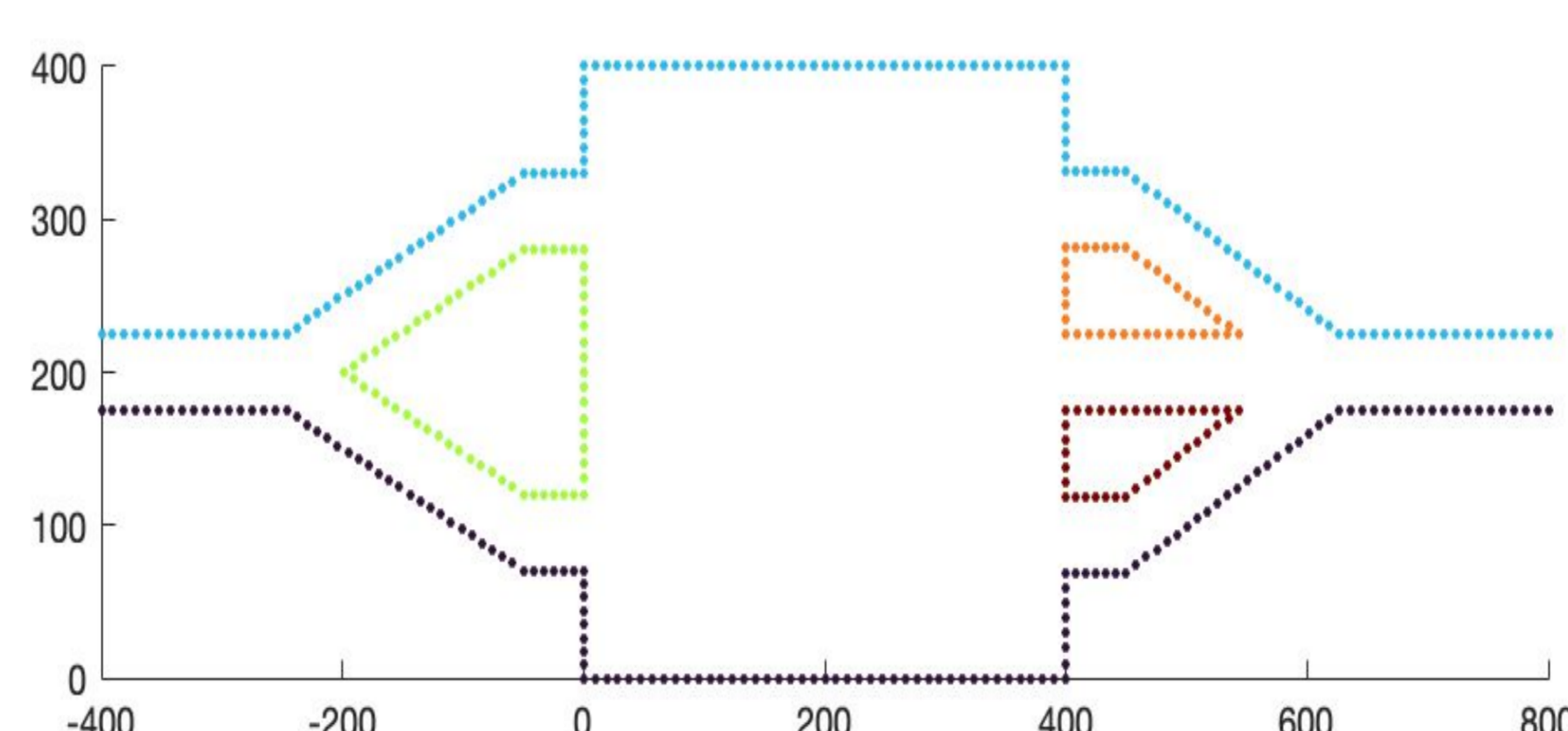


Figure 3: Example of combined redox flow manifold

## GAN Design

The first milestone when designing this GAN model was to be able to generate a singular line before working out generating internal geometries.

To do this, we trained a model based on the top lines of our generated manifolds (light blue line in fig. 3).

## Results

We were able to generate a line design using single point generation, and are currently in testing of a multi-point line generation GAN with varying levels of success.

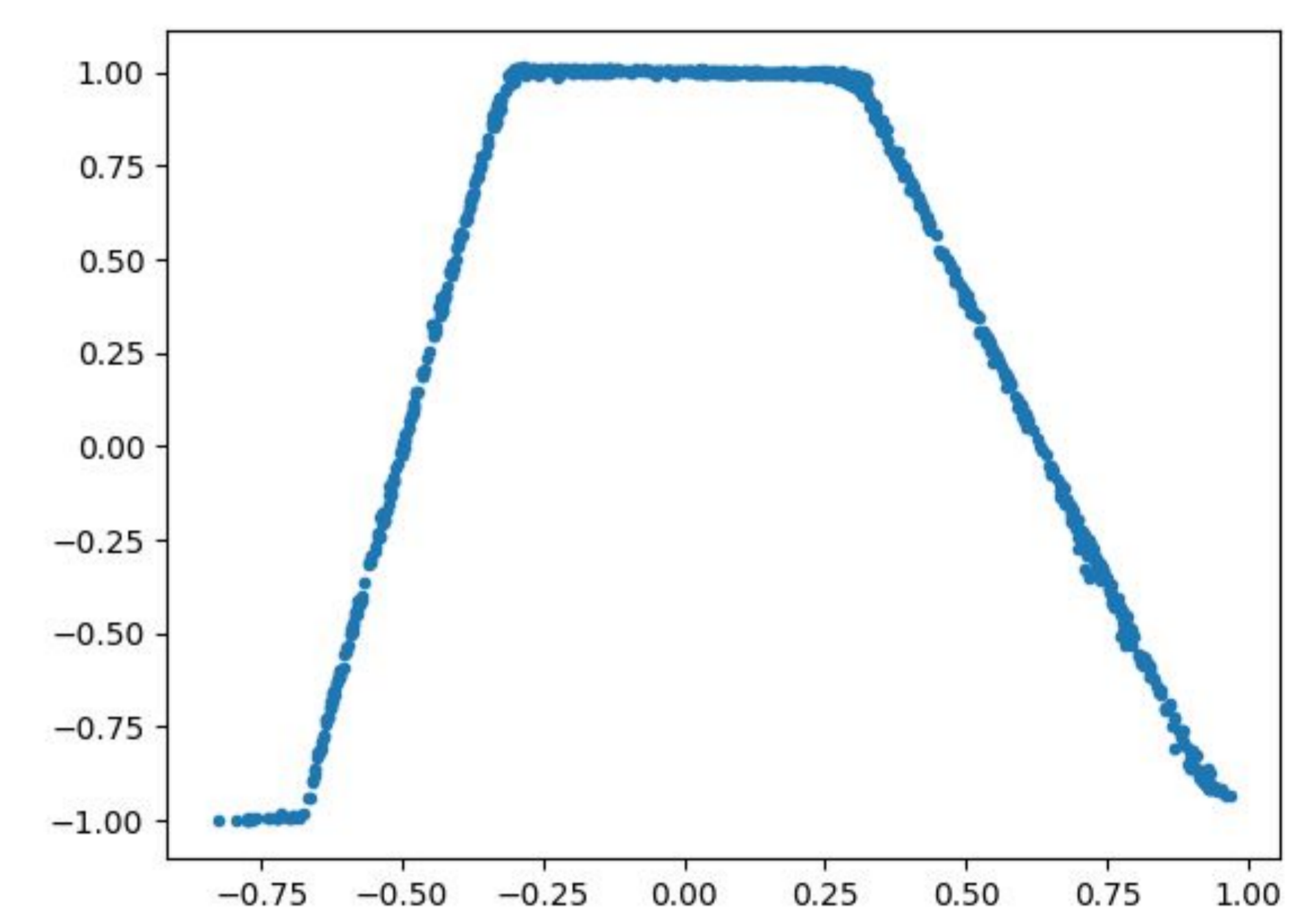


Figure 4: Example output of single point line generation

## Future Steps

- Finish testing line generation with output of 1024 points
- Update GAN to be capable of generating internal geometries
- Create a bezier layer to add smoothness to the sharp edges
- Integrate bayesian optimization for discovery of new redox flow battery channel topologies

## References

1. Chen, Wei & Chiu, Kevin & Fuge, Mark. (2019). Aerodynamic Design Optimization and Shape Exploration using Generative Adversarial Networks. 10.2514/6.2019-2351.
2. van Beek, Anton, et al. "Scalable adaptive batch sampling in simulation-based design with heteroscedastic noise." *Journal of Mechanical Design* 143.3 (2021): 031709.